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Vugdelija et al.

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(54) **PUPIL DETECTION**

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G06T 7/40	(2006.01)
G06K 9/62	(2006.01)

(52) **U.S. Cl.**

CPC ***G06K 9/0061*** (2013.01); ***G06K 9/6218*** (2013.01); ***G06T 7/0042*** (2013.01); ***G06T 7/408*** (2013.01); *G06T 2207/10024* (2013.01); *G06T 2207/30201* (2013.01)

(58) **Field of Classification Search**

USPC 382/115–118

See application file for complete search history.

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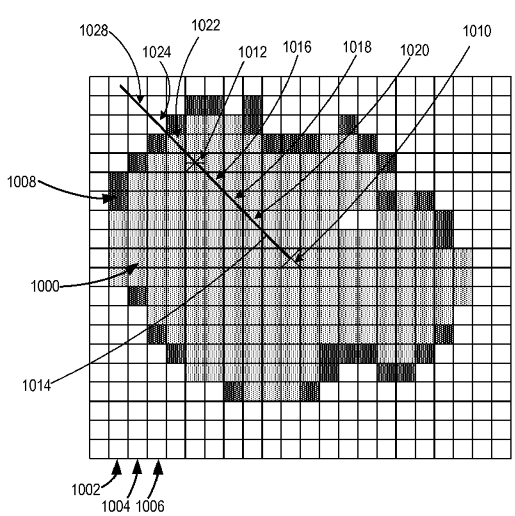
Primary Examiner — Alex Liew

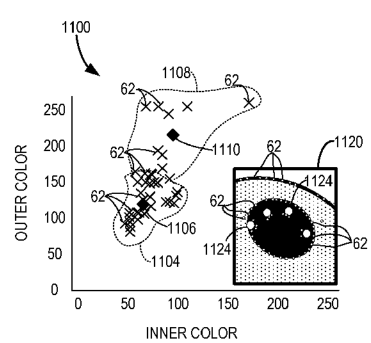
(74) *Attorney, Agent, or Firm* — Dan Choi; Judy Yee; Micky Minhas

(57) **ABSTRACT**

Embodiments that relate to determining an estimated pupil region of an eye are disclosed. In one embodiment a method includes receiving an image of an eye, with the image comprising a plurality of pixels. A rough pupil region is generated using at least a subset of the plurality of pixels. A plurality of pupil boundary point candidates are extracted from the rough pupil region, with each of the candidates weighted based on color values of at least two neighbor pixels. A parametric curve may be fitted to the weighted pupil boundary point candidates to determine the estimated pupil region of the eye of the user.

20 Claims, 10 Drawing Sheets





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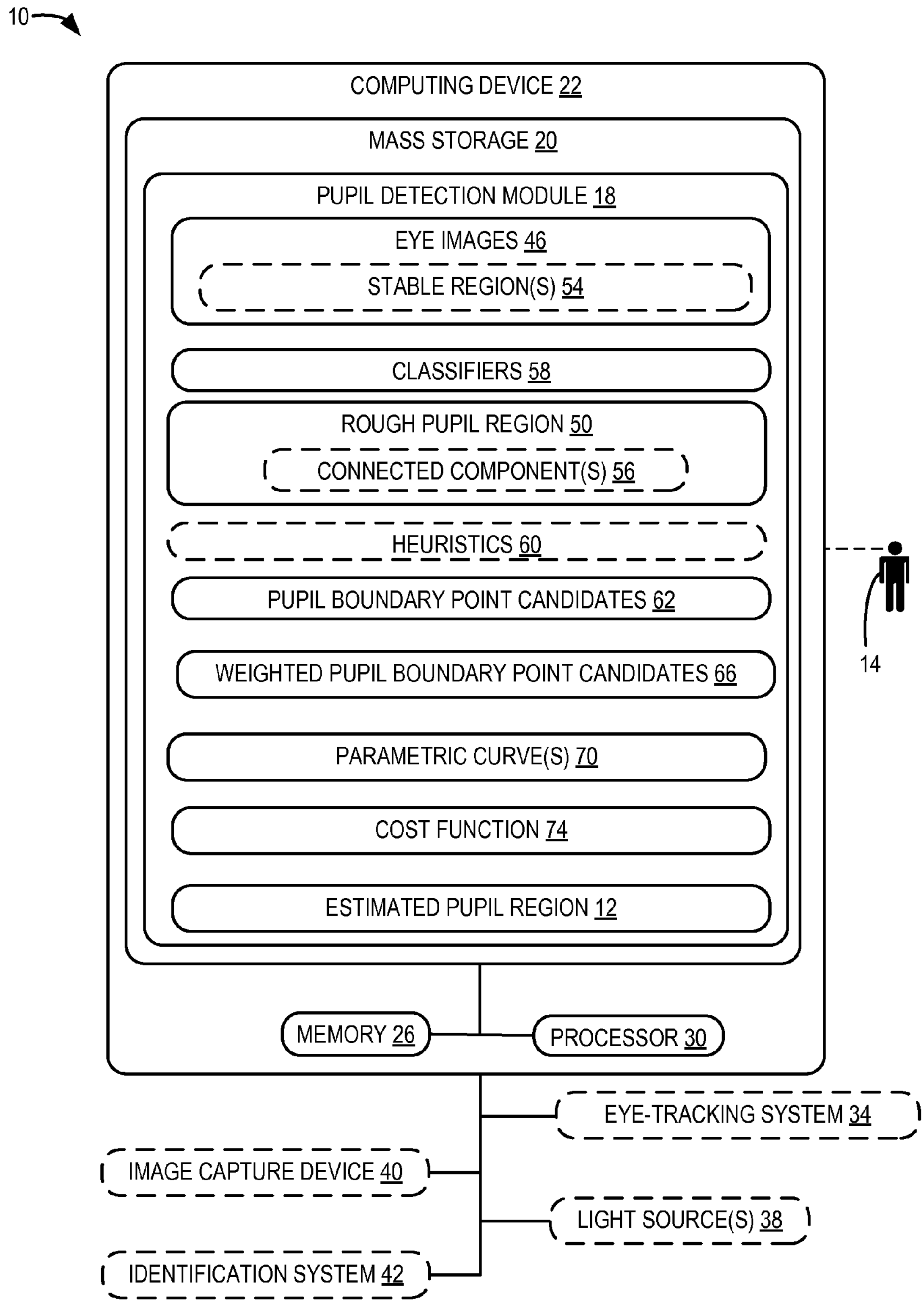

10
COMPUTING DEVICE 22
MASS STORAGE 20
PUPIL DETECTION MODULE 18
EYE IMAGES 46
STABLE REGION(S) 54
CLASSIFIERS 58
ROUGH PUPIL REGION 50
CONNECTED COMPONENT(S) 56
HEURISTICS 60
PUPIL BOUNDARY POINT CANDIDATES 62
WEIGHTED PUPIL BOUNDARY POINT CANDIDATES 66
PARAMETRIC CURVE(S) 70
COST FUNCTION 74
ESTIMATED PUPIL REGION 12
MEMORY 26
PROCESSOR 30
14
EYE-TRACKING SYSTEM 34
IMAGE CAPTURE DEVICE 40
LIGHT SOURCE(S) 38
IDENTIFICATION SYSTEM 42

FIG. 1

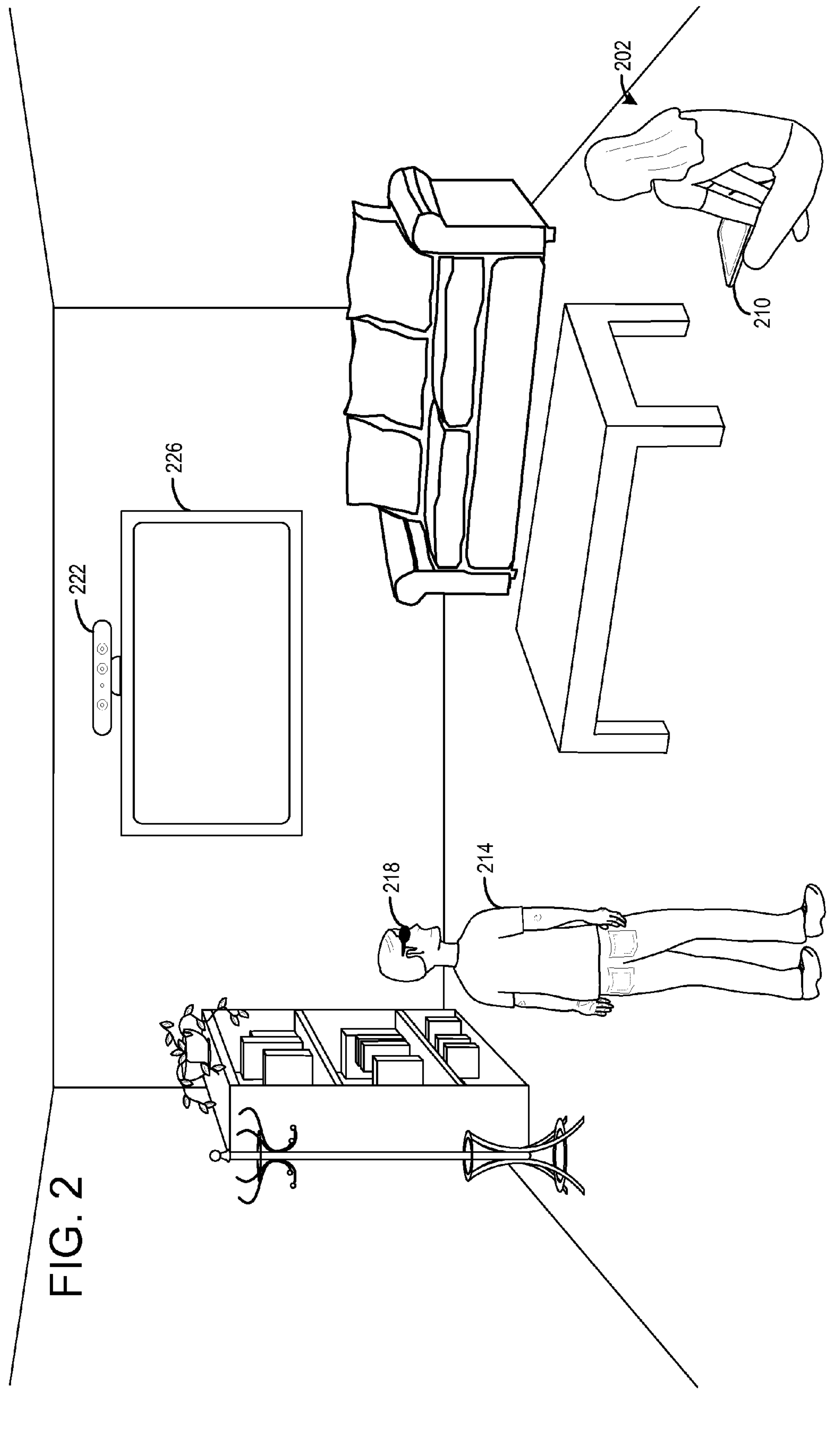


FIG. 2

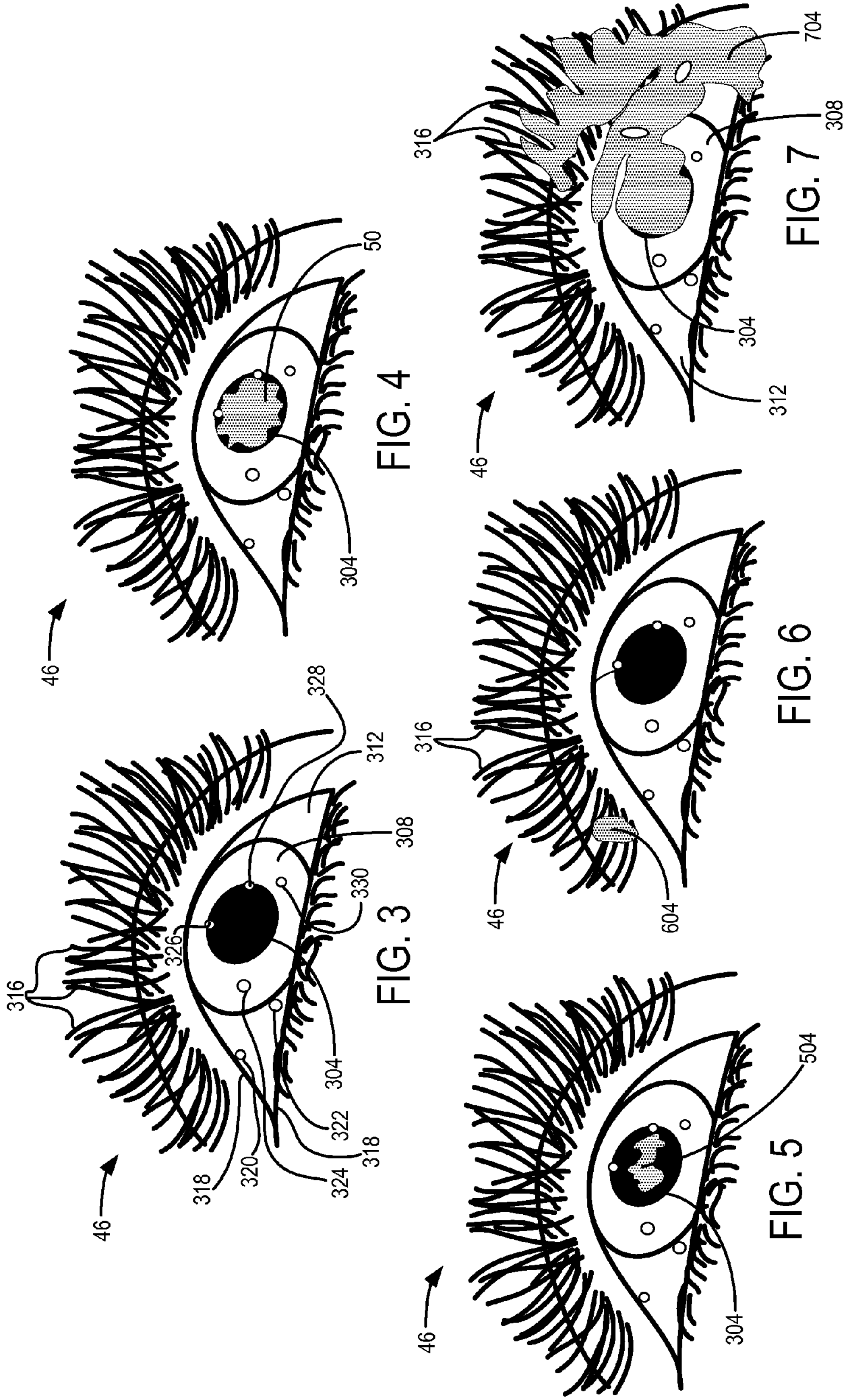


FIG. 3

FIG. 4

FIG. 5

FIG. 6

FIG. 7

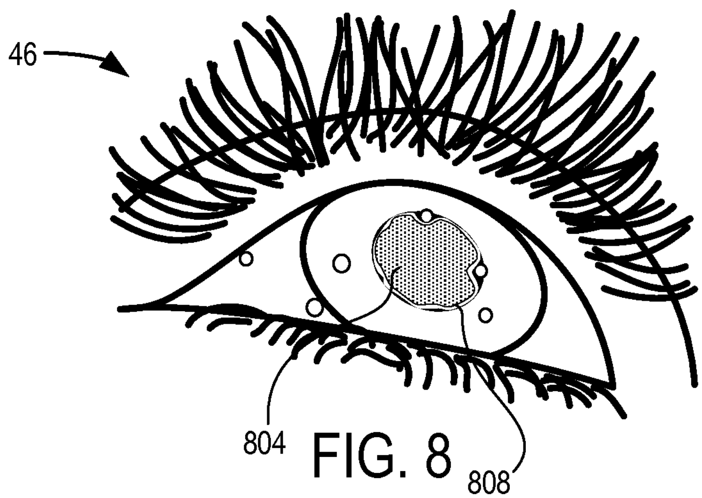


FIG. 8

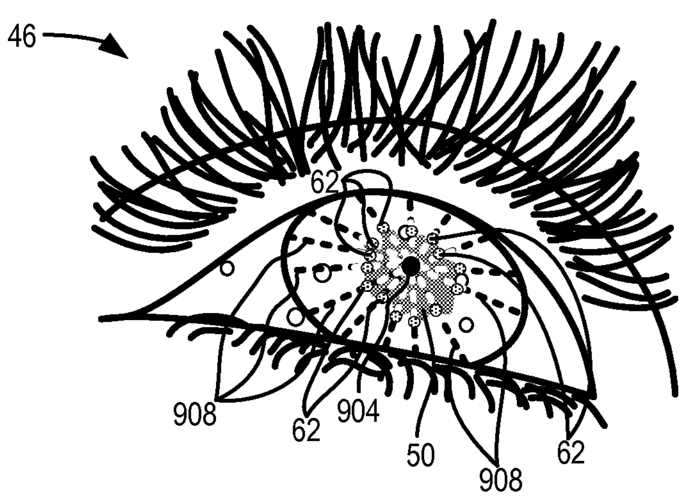


FIG. 9

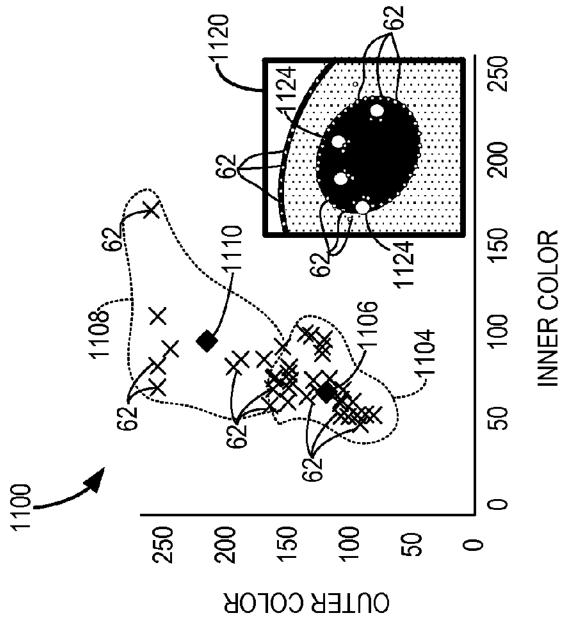

1100
1104
1106
1108
1110
1120
1124
62
OUTER COLOR
INNER COLOR
0
50
100
150
200
250

FIG. 11

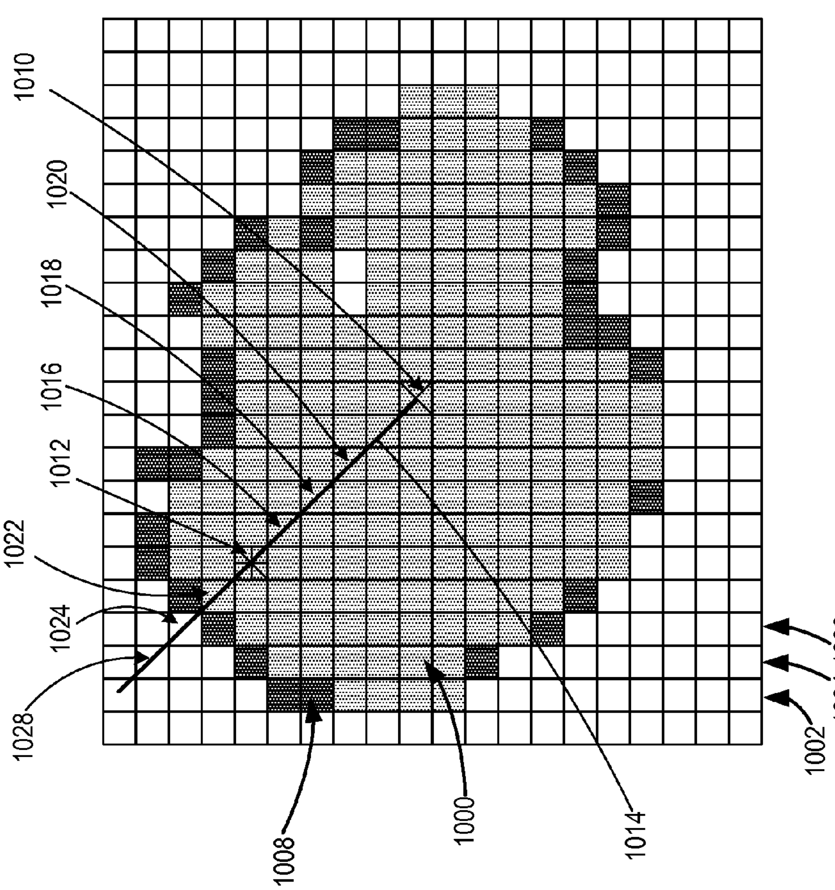

1000
1002
1004
1006
1008
1010
1012
1014
1016
1018
1020
1022
1024
1028

FIG. 10

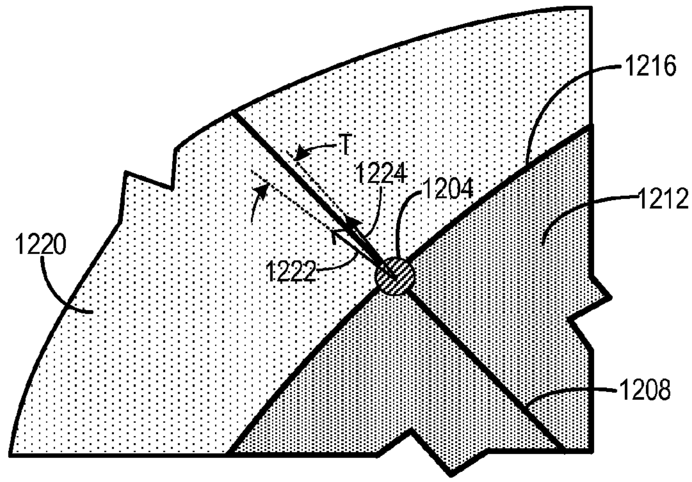


FIG. 12

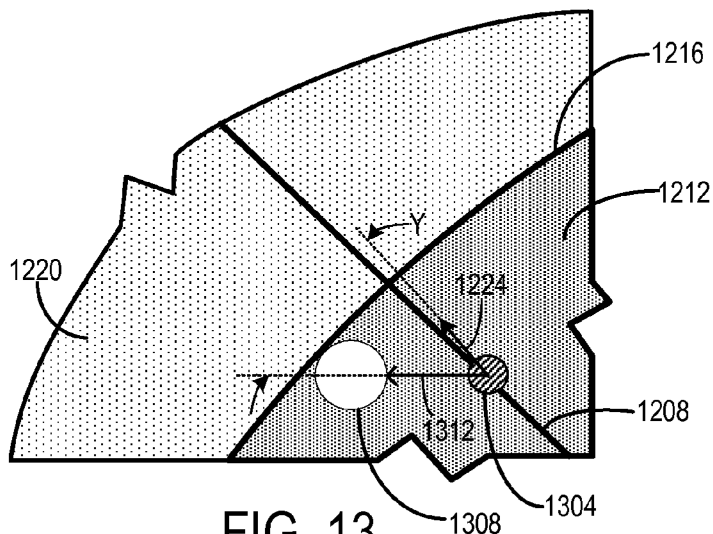


FIG. 13

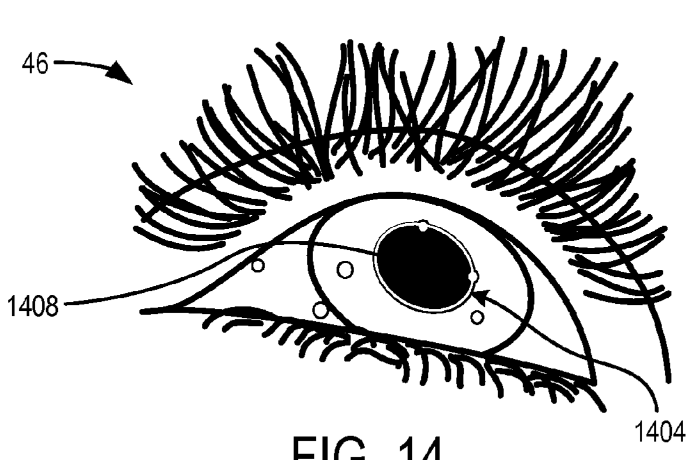


FIG. 14

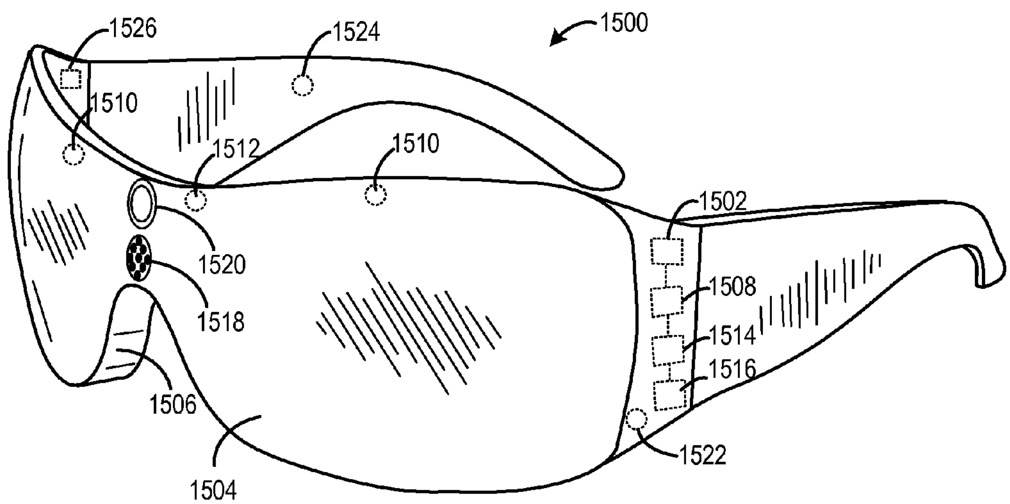

1500
1526
1524
1510
1512
1510
1502
1520
1518
1508
1514
1516
1506
1522
1504

FIG. 15

FIG. 16A

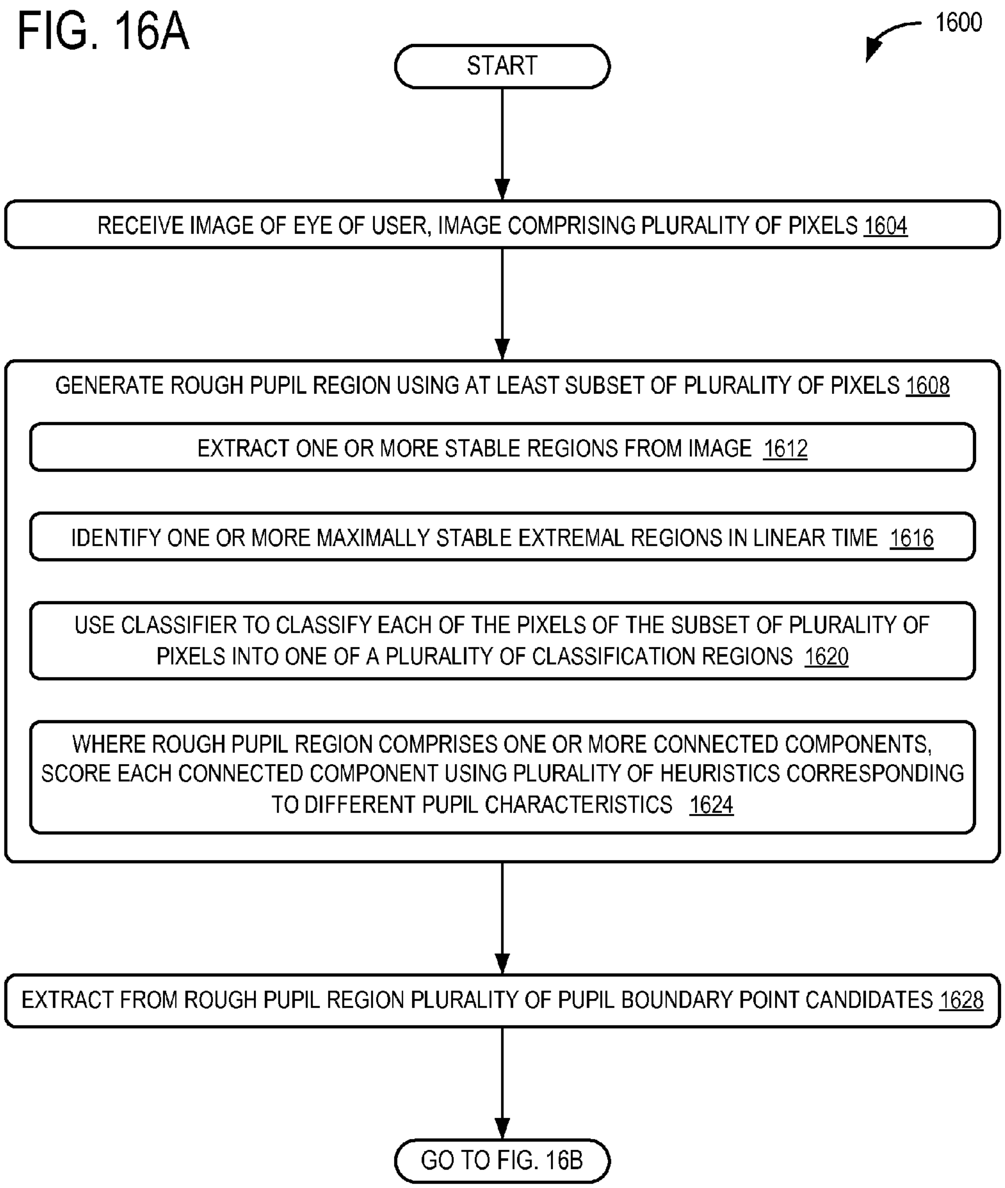
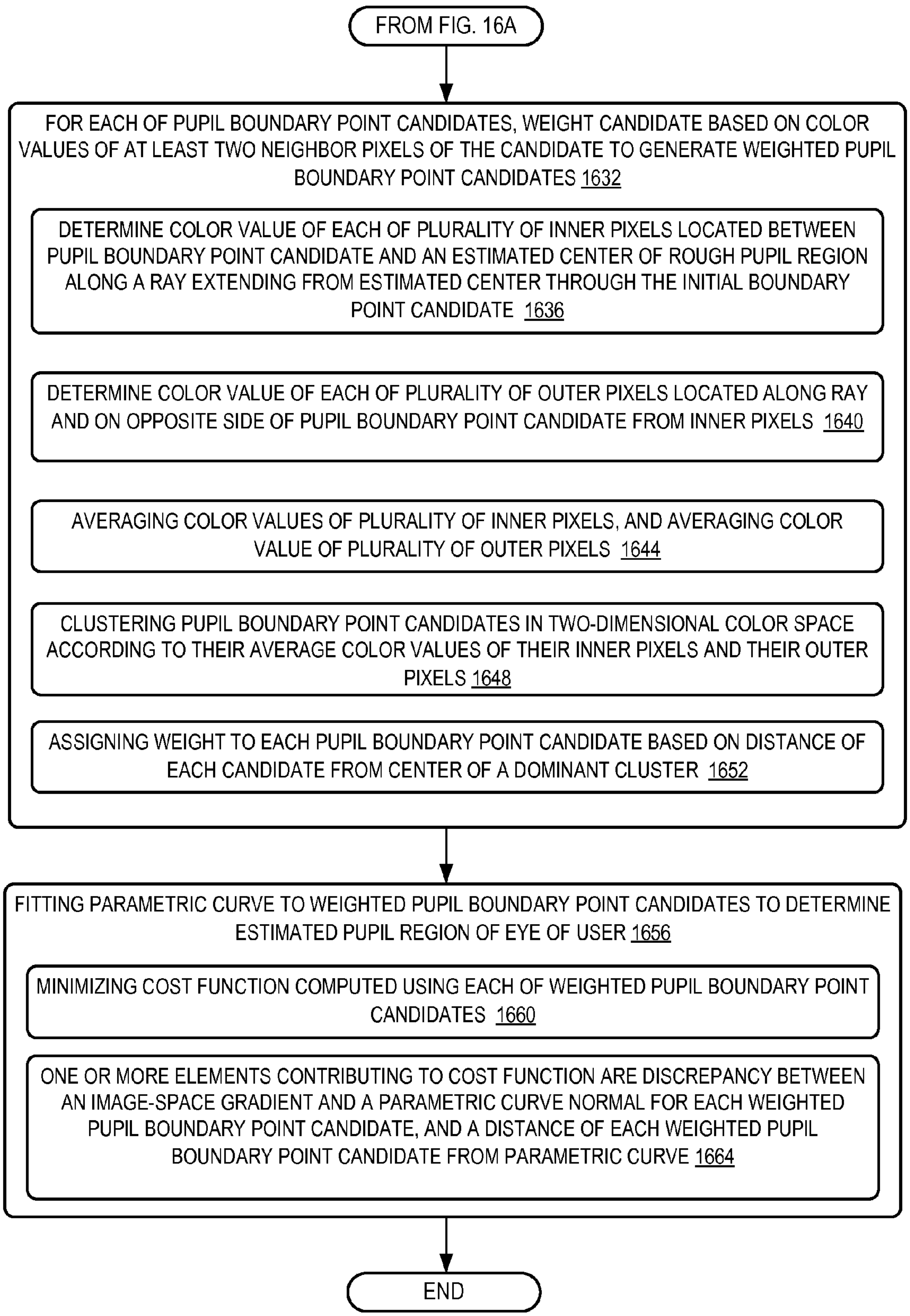

1600
START
RECEIVE IMAGE OF EYE OF USER, IMAGE COMPRISING PLURALITY OF PIXELS 1604
GENERATE ROUGH PUPIL REGION USING AT LEAST SUBSET OF PLURALITY OF PIXELS 1608
EXTRACT ONE OR MORE STABLE REGIONS FROM IMAGE 1612
IDENTIFY ONE OR MORE MAXIMALLY STABLE EXTREMAL REGIONS IN LINEAR TIME 1616
USE CLASSIFIER TO CLASSIFY EACH OF THE PIXELS OF THE SUBSET OF PLURALITY OF PIXELS INTO ONE OF A PLURALITY OF CLASSIFICATION REGIONS 1620
WHERE ROUGH PUPIL REGION COMPRISES ONE OR MORE CONNECTED COMPONENTS, SCORE EACH CONNECTED COMPONENT USING PLURALITY OF HEURISTICS CORRESPONDING TO DIFFERENT PUPIL CHARACTERISTICS 1624
EXTRACT FROM ROUGH PUPIL REGION PLURALITY OF PUPIL BOUNDARY POINT CANDIDATES 1628
GO TO FIG. 16B

FIG. 16B


FROM FIG. 16A
FOR EACH OF PUPIL BOUNDARY POINT CANDIDATES, WEIGHT CANDIDATE BASED ON COLOR VALUES OF AT LEAST TWO NEIGHBOR PIXELS OF THE CANDIDATE TO GENERATE WEIGHTED PUPIL BOUNDARY POINT CANDIDATES 1632
DETERMINE COLOR VALUE OF EACH OF PLURALITY OF INNER PIXELS LOCATED BETWEEN PUPIL BOUNDARY POINT CANDIDATE AND AN ESTIMATED CENTER OF ROUGH PUPIL REGION ALONG A RAY EXTENDING FROM ESTIMATED CENTER THROUGH THE INITIAL BOUNDARY POINT CANDIDATE 1636
DETERMINE COLOR VALUE OF EACH OF PLURALITY OF OUTER PIXELS LOCATED ALONG RAY AND ON OPPOSITE SIDE OF PUPIL BOUNDARY POINT CANDIDATE FROM INNER PIXELS 1640
AVERAGING COLOR VALUES OF PLURALITY OF INNER PIXELS, AND AVERAGING COLOR VALUE OF PLURALITY OF OUTER PIXELS 1644
CLUSTERING PUPIL BOUNDARY POINT CANDIDATES IN TWO-DIMENSIONAL COLOR SPACE ACCORDING TO THEIR AVERAGE COLOR VALUES OF THEIR INNER PIXELS AND THEIR OUTER PIXELS 1648
ASSIGNING WEIGHT TO EACH PUPIL BOUNDARY POINT CANDIDATE BASED ON DISTANCE OF EACH CANDIDATE FROM CENTER OF A DOMINANT CLUSTER 1652
FITTING PARAMETRIC CURVE TO WEIGHTED PUPIL BOUNDARY POINT CANDIDATES TO DETERMINE ESTIMATED PUPIL REGION OF EYE OF USER 1656
MINIMIZING COST FUNCTION COMPUTED USING EACH OF WEIGHTED PUPIL BOUNDARY POINT CANDIDATES 1660
ONE OR MORE ELEMENTS CONTRIBUTING TO COST FUNCTION ARE DISCREPANCY BETWEEN AN IMAGE-SPACE GRADIENT AND A PARAMETRIC CURVE NORMAL FOR EACH WEIGHTED PUPIL BOUNDARY POINT CANDIDATE, AND A DISTANCE OF EACH WEIGHTED PUPIL BOUNDARY POINT CANDIDATE FROM PARAMETRIC CURVE 1664
END

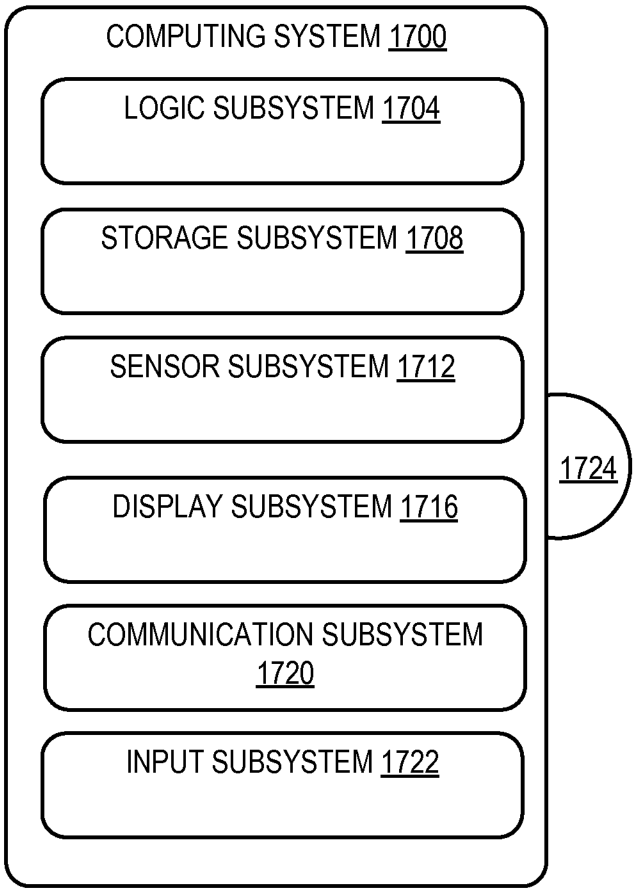

COMPUTING SYSTEM 1700
LOGIC SUBSYSTEM 1704
STORAGE SUBSYSTEM 1708
SENSOR SUBSYSTEM 1712
DISPLAY SUBSYSTEM 1716
COMMUNICATION SUBSYSTEM 1720
INPUT SUBSYSTEM 1722
1724

FIG. 17

PUPIL DETECTION

Images of a person's eye may be utilized for a variety of purposes, from personal identification to human-computer interaction. For example, eye or gaze tracking systems may utilize captured images of a person's eye to determine a direction and/or location of the person's gaze. In some examples, such gaze tracking or other systems utilize the location and/or shape of the pupil of the eye.

However, one or more portions of the pupil may be obscured or occluded by an eyelid, eyelashes, glints, external reflections or other light sources, and/or other conditions. Accordingly, the accuracy of an estimated direction of a person's gaze, eye-based identity of a person, or other determination that utilizes pupil location and/or shape may suffer. Additionally, accounting for such conditions in estimating a pupil location and/or shape may prove computationally expensive.

SUMMARY

Various embodiments are disclosed herein that relate to systems and methods for determining an estimated pupil region of an eye. For example, one disclosed embodiment provides a method for determining an estimated pupil region of an eye of a user in which an image of the eye is received, with the image comprising a plurality of pixels. A rough pupil region may be generated using at least a subset of the plurality of pixels.

A plurality of pupil boundary point candidates may be extracted from the rough pupil region. Each of the candidates may be weighted based on color values of at least two neighbor pixels of the candidate to generate weighted pupil boundary point candidates. A parametric curve may be fitted to the weighted pupil boundary point candidates to determine the estimated pupil region of the eye of the user.

This Summary is provided to introduce a selection of concepts in a simplified form that are further described below in the Detailed Description. This Summary is not intended to identify key features or essential features of the claimed subject matter, nor is it intended to be used to limit the scope of the claimed subject matter. Furthermore, the claimed subject matter is not limited to implementations that solve any or all disadvantages noted in any part of this disclosure.

BRIEF DESCRIPTION OF THE DRAWINGS

FIG. **1** is a schematic view of a system for determining an estimated pupil region of an eye according to examples of the present disclosure.

FIG. **2** is a schematic perspective view of a room including a user wearing a head-mounted display device, a user holding a tablet computer, and a wall-mounted display according to examples of the present disclosure.

FIG. **3** is a schematic view of an image of a user's eye including several glints.

FIG. **4** is a schematic view of the image of FIG. **3** including a rough pupil region that is generated according to an example of the present disclosure.

FIGS. **5**, **6** and **7** are schematic views of the image of FIG. **3** showing example maximally stable extremal regions that are identified according to examples of the present disclosure.

FIG. **8** is a schematic view of a connected component boundary of the rough pupil region of FIG. **4** obtained according to an example of the present disclosure.

FIG. **9** is a schematic view showing pupil boundary point candidates extracted from the rough pupil region of FIG. **4** according to an example of the present disclosure.

FIG. **10** is a schematic illustration of a rough pupil region and a pupil boundary point candidate located on a ray extending from an estimated center of the rough pupil region according to an example of the present disclosure.

FIG. **11** is schematic diagram of a two-dimensional color space showing pupil boundary point candidates distributed via a k-means clustering algorithm according to an example of the present disclosure.

FIG. **12** is a schematic illustration of a portion of a rough pupil region and a pupil boundary point candidate located on a ray extending from an estimated center of the region

FIG. **13** is a schematic illustration of another portion of a rough pupil region and another pupil boundary point candidate located on a ray extending from an estimated center of the region.

FIG. **14** is a schematic illustration of a parametric curve corresponding to an estimated pupil region that is determined according to an example of the present disclosure.

FIG. **15** schematically shows an example head-mounted display device according to an example of the present disclosure.

FIGS. **16**A and **16**B are a flow chart of a method for determining an estimated pupil region of an eye of a user according to an example of the present disclosure.

FIG. **17** is a simplified schematic illustration of an example of a computing system.

DETAILED DESCRIPTION

FIG. **1** shows a schematic view of one embodiment of a system **10** for determining an estimated pupil region **12** of an eye of a user **14**. The system **10** includes a pupil detection module **18** that may be stored in mass storage **20** of a computing device **22**. The pupil detection module **18** may be loaded into memory **26** and executed by a processor **30** of the computing device **22** to perform one or more of the methods and processes described in more detail below.

In some examples, the computing device **22** may be communicatively coupled to one or more other devices and/or components. For example, the computing device **22** may be communicatively coupled to an eye-tracking system **34** that may utilize an estimated pupil region **12** that is determined by the pupil detection module **18**. In some examples, the eye-tracking system **34** may utilize one or more light source(s) **38**. In some examples the light source(s) **38** may comprise infrared light sources that emit infrared light, such as an infrared LED. In other examples the light source(s) **38** may comprise visible light sources that emit visible light, such as a visible LED. The eye-tracking system **34** may further include one or more image capture devices **40** that are configured to capture images of the light that is reflected and scattered from an eye of a user.

In other examples, the computing device **22** may be communicatively coupled to an identification system **42** that may utilize an estimated pupil region **12** determined by the pupil detection module **18** to determine an identity of a user **14**. It also will be appreciated that the computing device **22** may be utilized with others device(s) or component(s) that may utilize an estimated pupil region **12** that is determined and output by the pupil detection module **18**.

In some examples, the computing device **22** and one or more of the eye-tracking system **34**, light source(s) **38**, image capture device(s) **40**, and identification system **42** may be integrated into a common enclosure to form a single device.

Such devices may include, but are not limited to, desktop computers, PCs, hand-held smart phones, e-readers, laptop, notebook and tablet computers, head-mounted display (HMD) devices, peripheral displays, interactive televisions, set-top boxes, gaming consoles, etc.

For example and with reference to FIG. **2**, a tablet user **202** may utilize a tablet **210** that comprises system **10**. Another user **214** may wear an HMD device **218**, described in more detail below, that incorporates system **10**. In other examples, one or more of the eye-tracking system **34**, identification system **42**, light source(s) **38**, and image capture device(s) **40** may be physically separate from and communicatively coupled to the computing device **22**. In one example, one or more of these components may be located in an input device **222** mounted adjacent to a wall-mounted display **226**, and may be communicatively coupled to a computing device **22** in the display or in a separate component, such as a gaming console, via a wired or wireless connection.

It will be appreciated that many other types and configurations of system **10** having various form factors, whether separate from or integrated with a computing device **22**, may also be used and are within the scope of the present disclosure. Additional details regarding the components and computing aspects of the computing device **22** are described in more detail below with reference to FIG. **17**.

With reference again to FIG. **1**, in some examples the eye-tracking system **34** may be configured to utilize an estimated pupil region **12** generated by the pupil detection module **18**, as described in more detail below, to determine a gaze direction of a user's eye in any suitable manner. For example, the eye-tracking system **34** may utilize images of the pupil and corneal reflections that generate corneal glints captured by the image capture device(s) **40** to determine a center of the pupil and locations of the glints. The corneal glints may be used to determine a position of the cornea. Pupil images then may be used to find an orientation of the cornea based on the glints, and a gaze vector of the eye may be determined.

In one example a bright pupil technique may be utilized in which the illuminated light from the light source(s) **38** is coaxial with the optical path of the eye, causing the light to reflect off the retina. In other examples, a dark pupil technique may be utilized in which the illuminated light is offset from the optical path.

Images of corneal glints and of the pupil as determined from image data gathered from the image capture device(s) **40** may be used to determine an optical axis of an eye. Using this information, the eye-tracking system **34** may determine a direction and/or at what physical object or virtual object the user is gazing. The eye-tracking system **34** may further determine at what point on a physical or virtual object the user is gazing. Such gaze tracking data may then be provided to the computing device **22**, and may be utilized by one or more applications or other programs as needed.

In some examples and as noted above, computing device **22** may be communicatively coupled with a head-mounted display (HMD) device, such as HMD device **218** shown in FIG. **2**. The HMD device **218** may comprise a transparent, semi-transparent or non-transparent display that is supported in front of a viewer's eye or eyes. In some examples, the HMD device **218** may create and display to a user **214** an augmented reality environment that includes one or more computer generated images that are displayed among one or more real-world objects in a physical environment viewed through the device. The computer generated images may comprise three-dimensional (3D) holographic images, two-dimensional (2D) images, or other forms of virtual images that are generated and displayed via HMD device **218**. The HMD device **218** may thereby enable the user **214** to view such computer generated images within the physical environment surrounding the viewer.

As described in more detail below, the HMD device **218** may include various sensors and related systems that receive physical environment data from the physical environment. For example, the HMD device **218** may include a depth sensor system that includes one or more depth cameras that generate depth image data from real-world objects in the surrounding physical environment. In some examples the HMD device **218** may include an optical sensor system that utilizes at least one outward facing sensor, such as an RGB camera or other optical sensor. The outward facing sensor may capture two-dimensional image information from real-world objects in the physical environment. The HMD device **218** may also include a position sensor system comprising one or more accelerometers, gyroscopes, head tracking systems, and/or other sensors for determining a position or orientation of a user.

In some examples the HMD device **218** may include a transducer system comprising one or more actuators that convert an electrical signal into another form of energy. The transducer system may include one or more speakers for providing audio feedback to a viewer. In other examples the transducer system may include one or more tactile transducers for generating and providing haptic feedback to the viewer, such as vibrations. The HMD device **218** may also include a microphone system and one or more microphones for receiving audio input from the physical environment.

The example HMD device **218** illustrated in FIG. **2** may include the computing device **22** integrated into the HMD device. It will be appreciated that in other examples the computing device **22** may be a separate component from the HMD device **218**. Many types and configurations of HMD devices having various form factors also may be used and are within the scope of the present disclosure. A more detailed description of an example HMD device is provided below with reference to FIG. **15**.

With reference now also to FIGS. **3-14**, descriptions of example use cases of the system **10** and pupil detection module **18** will now be provided. In one example schematically shown in FIG. **3**, an image **46** of a user's eye may be received by the pupil detection module **18**. The image **46** may comprise a plurality of pixels, and may show various features of the eye such as the pupil **304**, iris **308**, sclera **312**, eyelashes **316**, and eyelids **318**. The image may also comprise one or more glints that are created when external light impinges upon and is reflected by the front corneal surface of the eye. Such reflections appear as intense areas (glints) in the image **46**. The example of FIG. **3** shows glints **320**, **322**, **324**, **326**, **328**, and **330** located at various positions in the image **46**.

As noted above, in some cases one or more eyelashes **316**, eyelids **318**, glints, and/or other obstructions may occlude or obscure a portion of the pupil **304**, potentially making reliable identification of pupil location and shape challenging. As described in more detail below, the system **10** and pupil detection module **18** of the present disclosure may reliably determine an estimated pupil region of a user's eye, even when portions of the pupil **304** in a pupil image are occluded or otherwise compromised. The system **10** and pupil detection module **18** of the present disclosure may also determine such regions using less computational resources than previous systems.

With reference now to FIG. **4**, the pupil detection module **18** may be configured to use at least a subset of the pixels of the eye image **46** to generate a rough pupil region **50** that provides an initial approximation of the actual location and shape of the pupil **304** of the eye. In some examples, the pupil detection module **18** may generate potential rough pupil regions by extracting one or more stable regions **54** from the eye image **46**. For example, the pupil detection module **18** may be configured to identify one or more maximally stable extremal regions (MSERs). In some examples, one or more MSERs may be identified in linear time.

An MSER may be defined as a connected component within the image region that contains pixels significantly lighter (or darker) than pixels outside of the component boundary. Local binarization is stable in an MSER over a large range of thresholds. Accordingly and in some examples, beginning with a seed pixel and a predetermined color intensity threshold, an MSER representing a potential pupil region may be determined. As the color intensity threshold is varied over a defined range, if the spatial extent of the region changes (expands/contracts) by an amount less than a stability threshold, then the connected component may be identified as an MSER.

Any of a variety of approaches for extracting MSERs from the image **46** may be utilized. In some examples, pixels considered or visited at any point during computation of an MSER may consist of a single connected component **56** of pixels in the image, resembling a flood-fill that adapts to the grey-level landscape. The computation may use a priority queue of candidate pixels (the boundary of the single connected component), a single bit image masking visited pixels, and information for as many components as there are grey-levels in the image. In this manner, a component tree of connected components of the image may be generated in true linear time. Further, by working with a single connected component of pixels, less memory is used and execution is faster as compared to other algorithms for computing MSERs.

FIGS. **5**-**8** show examples of different MSERs that may be identified in the eye image **46** in a manner as described above. For example, FIG. **5** illustrates an MSER **504** that is located within the pupil **304**. FIG. **6** illustrates an MSER **604** that is located within eyelashes **316**. FIG. **7** illustrates a larger MSER **704** that covers portions of the pupil **304**, iris **308**, sclera **312**, eyelids **318** and eyelashes **316**.

In other examples, potential rough pupil regions **50** may be identified in different manners. For example, a Haar-like detection approach may be utilized in which an input image may be convoluted with a pupil-like template image. Pixels with a high convolution response may be isolated as potential pupil centers. Simple template images may be utilized such as, for example, a black pupil-sized circle or rectangle on a white background. Connected components **56** representing potential rough pupil regions **50** may be isolated using adaptive binarization.

In other examples, the pupil detection module **18** may generate potential rough pupil regions by using one or more classifiers **58** to classify each of the pixels of the subset of pixels into one of a plurality of classification regions. The classes or regions may include, but are not limited to, pupil, iris, sclera, eyelash, background, and glint. The classifier(s) may be trained on a labeled dataset comprising images of human eyes. In some examples, the classification may be a random forest classifier. Given a large set of ground truth input, optimal questions are chosen at each node of a decision tree so that input samples are classified optimally at the end of the leaves. This trained data base may be used to predict the classification of each pixel in the input image.

The questions learned during training may be evaluated for each pixel, and depending on the response (either positive or negative), the next node of the decision tree is chosen and the next question is asked. The questions may include determining a pixel difference from one or more neighbor pixels of the subject pixel. For example, for a subject pixel an x-y color offset with respect to a neighbor pixel may be determined. The offset may be compared to a threshold and, based on the comparison, another question is evaluated for the subject pixel. Those questions that yield the largest separations between classes are selected. This process is repeated until a leaf node that predicts the classification is reached. The classifier outputs the results of the classes of the pixels, which are then grouped into one or more connected components **56** and a rough pupil region **50** is extracted.

In some examples, the MSERs and/or other connected components may be scored against a plurality of heuristics **60** that favor pupil characteristics, such as pupil size, shape, expected location, relative color, and/or other characteristics that suggest a pupil. Such heuristics **60** may include, but are not limited to, a pupil aspect ratio, a quantity of holes inside the connected component, a gradient intensity on a boundary of the connected component, a rate of change of consecutive pixel rows or pixel columns of the connected component, an average color intensity of the one or more connected components as compared to the connected component's surrounding, a distance between a centroid of the one or more connected components and a center of the eye image **46**, a size of the one or more connected components relative to a size of its bounding rectangle, and a size of the one or more connected components relative to a size of the eye image **46**.

With reference to the connected component **1000** illustrated in FIG. **10**, an example of the heuristic **60** regarding the rate of change of consecutive horizontal pixel rows or consecutive vertical pixel columns of the connected component is now provided. Moving from left to right, the illustrated component **1000** has 4 pixels in its first column **1002**, 6 in its second column **1004**, 9 pixels in its third column **1006**, and so on. Accordingly, when moving from the first column **1002** to the second column **1004**, the change of consecutive vertical pixel columns is 6-4=2. When moving from second column **1004** to the third column **1006**, the change of consecutive vertical pixel columns is the change is 9-6=3, and so on. The pupil detection module **18** may compute the average change between consecutive columns for the component **1000**, and compare this average to a heuristic corresponding to the average change between consecutive columns of a pupil image.

Accordingly, by scoring each of the MSERs and/or other connected components against a plurality of heuristics **60** that favor pupil characteristics, the highest-scoring component may be selected as the rough pupil region **50**. An example of a selected rough pupil region **50** is schematically illustrated in FIG. **4**.

In the above examples of determining a rough pupil region **50**, an eye image **46** that has been downscaled from a full resolution image may be utilized. In this manner, the computational resources needed to determine the rough pupil region **50** may be reduced. In one non-limiting example, for a full resolution image having a size of 640×480 pixels, the above methods may operate on a downscaled version of the image having a size of 80×60 pixels, or any other suitable lower resolution image. In other examples, the above examples may utilize the full resolution image without downscaling the image.

Using the generated rough pupil region **50**, the pupil detection module **18** may extract from the rough pupil region a plurality of pupil boundary point candidates **62**. With reference now to FIG. **8**, in some examples adaptive binarization may be performed on the rough pupil region **50** to generate a pupil connected component **804**. A component boundary **808** comprising pupil boundary point candidates **62** may be extracted from the pupil connected component **804**. In other examples, color information obtained from a rough pupil region **50** may be used to compute a binarization threshold that may be applied to isolate a pupil mask. Pupil boundary point candidates **62** may be extracted from such a mask.

In some examples and with reference to FIG. **9**, a center **904** of the rough pupil region **50** detected above may be determined, and a number of rays **908** may be cast radially from the center. It will be appreciated that along each of these rays **908** at the boundary between the actual pupil and the iris in the image, an area of sudden color intensity change will exist. Accordingly, the pupil detection module **18** may evaluate each ray **908** and the rough pupil region **50** to identify areas of sudden color intensity change. The pupil detection module **18** may then extract a pupil boundary point candidate **62** corresponding to each such area.

Each of the extracted areas may correspond to a pupil boundary point candidate **62** that is potentially located at the pupil-iris boundary. In some cases, however, one or more pupil boundary point candidates **62** may not be located at the pupil-iris boundary, and thus may constitute false positives. Such false positives may be created by a glint or other occlusion in the eye image **46**. Accordingly and as described in more detail below, the pupil detection module **18** may, for each of the pupil boundary point candidates **62**, weight the pupil boundary point candidate based on color values of at least two neighbor pixels of the pupil boundary point candidate to generate weighted pupil boundary point candidates **66**.

In some examples, a common property of false positive pupil boundary point candidates is that the color surrounding the candidate differs significantly from color surrounding true pupil boundary point candidates that are located at the pupil-iris boundary. For example and with reference to FIG. **13**, a false positive pupil boundary point candidate **1304** located near a glint **1308** may be identified based on the high contrast of the white glint, as compared to the lower contrast of the iris region **1220** which typically will be a shade of gray that corresponds to the iris color.

Accordingly and in some examples, each of the pupil boundary point candidates **62** may be weighted based on color values of at least two neighbor pixels. With reference now to FIG. **10**, a schematic illustration of a connected component **1000** comprising a rough pupil region that is shown overlying a pupil image **1008** is provided. The rough pupil region includes an estimated center pixel **1010** and a pupil boundary point candidate pixel **1012** located on a ray **1014** extending from the estimated center pixel **1010**. Located along the ray **1014** and on either side of the pupil boundary point candidate pixel **1012** are neighbor pixels of the pupil boundary point candidate pixel.

In one example, the pupil detection module **18** may determine a color value of each of a plurality of inner pixels located between the pupil boundary point candidate **1012** and the estimated center pixel **1010** along the ray **1014**. In some examples, the pupil detection module **18** may average the color values of two, three, four, or any suitable number of inner pixels located between the pupil boundary point candidate **1012** and the estimated center pixel **1010** along the ray **1014**. With reference to the example of FIG. **10**, in one example the color values of inner pixels **1016**, **1018**, and **1020** may be averaged to determine an average color value.

Similarly, the pupil detection module **18** may average the color values of two, three, four, or any suitable number of outer pixels located on an opposite side of the pupil boundary point candidate **1012** from the inner pixels along the ray **1014**. With reference to the example of FIG. **10**, in one example the color values of outer pixels **1022**, **1024**, and **1028** may be averaged to determine an average color value.

With reference now to FIG. **11**, the plurality of pupil boundary point candidates **62** may be mapped to a two-dimensional color space **1100**, where the x-axis represents the candidate's inner color (the color along the ray **1014** from the candidate towards the estimated center pixel **1010**), while the y-axis represents the candidate's outer color (the color along the ray **1014** from the candidate away from the estimated center pixel). Most pupil boundary point candidates **62** will group in this color space around a point most likely to represent pupil color (along the inner color axis) and iris color (along the outer color axis). The pupil boundary point candidates **62** that are false positives will be spread around the color space **1100**.

In some examples, a clustering algorithm may be utilized to weight pupil boundary point candidates **62** according to their distance from an estimated center of a dominant cluster. For example and as schematically illustrated in FIG. **11**, a k-means clustering algorithm with k=2 may be used to assign a weight to each of the pupil boundary point candidates. Also in FIG. **11**, an inset image **1120** schematically shows the location of pupil boundary point candidates **62** and glints **1124** in a portion of an image **46**.

As shown in FIG. **11**, applying k-means clustering with k=2 to the color values of a plurality of pupil boundary point candidates **62** yields a first cluster **1104** of points and a second cluster **1108** of points in the color space **1100**. The first cluster **1104** may have a center **1106**, and the second cluster **1108** may have a center **1110**. In FIG. **11** the vertical "outer color" axis may represent an average color value of a plurality of outer pixels of a pupil boundary point candidate, and the horizontal "inner color" axis may represent an average color value of a plurality of inner pixels of the pupil boundary point candidate.

In the present examples, the first cluster **1104** may contain a larger number of pupil boundary point candidates **62** than second cluster **1108**. Accordingly, the first cluster **1104** may be identified and utilized as the dominant cluster. For each of the pupil boundary point candidates **62**, a distance from the center **1106** of the first, dominant cluster **1104** may be calculated. Using such distance, a corresponding weight for that pupil boundary point candidate **62** may be determined and assigned to the candidate. In this manner, pupil boundary point candidates **62** with an inner color and an outer color that are more similar to the dominant cluster center **1106** will be assigned higher weights. Correspondingly, pupil boundary point candidates **62** with an inner color and an outer color that are less similar to the dominant cluster center **1106** will be assigned lower weights. Accordingly, in this manner the pupil detection module **18** may weight each of the pupil boundary point candidates **62** to generate weighted pupil boundary point candidates **66**.

In some examples, and in one potential advantage of the present disclosure, the pupil detection module **18** may utilize every pupil boundary point candidate **62** in determining an estimated pupil region of the eye of a user. Correspondingly, the pupil detection module **18** may avoid discarding any of the pupil boundary point candidates **62**, regardless of their distance from the dominant cluster center **1106**. In other examples, one or more weighted pupil boundary point candidates **66** having weights below a low weight threshold may be discarded.

Using the weighted pupil boundary point candidates **66**, the pupil detection module **18** may fit a parametric curve **70** to the weighted pupil boundary point candidates to determine an estimated pupil region **12** of the eye of a user. In this manner, the pupil detection module **18** may find a boundary of the estimated pupil region **12** expressed as a parametric curve **70**.

In some examples, a parametric curve may be defined by an equation F(x, y, P)=0, where x and y are two-dimensional image space coordinates of pupil boundary point candidates **62**, and P is a set of parameters to be determined. For example, the parameters P may be determined by randomly selecting a subset of pupil boundary point candidates **62** and fitting a parametric curve **70** through those points. Repeating this approach a fixed number of iterations and scoring each curve against all of the pupil boundary point candidates may yield an approximation of a pupil boundary that defines an estimated pupil region **12**.

In some examples this approach may be made iterative. For example, a Random Sample Consensus (RANSAC) algorithm may be utilized to estimate the parameters P from the set of pupil boundary point candidates **62** that contains outliers. In some examples additional pupil boundary point candidates that have small errors may also be included, and a least squares method may be utilized to obtain a more accurate model. It will be appreciated that other suitable iterative methods and algorithms also may be utilized. In some examples, the parametric curve **70** that achieves the highest score against all of the pupil boundary point candidates **62** may be used as a final result to determine the estimated pupil region **12** of the eye of the user.

In other examples, the highest-scoring parametric curve **70** may serve as a starting point of an iterative optimization algorithm such as, for example, a Levenberg-Marquardt algorithm (LMA). In this class of algorithms, the set of parameters P may be changed at each iteration in the direction of fastest decay of a cost function **74**. The resulting parametric curve **70** may be used as a final result to determine the estimated pupil region **12** of the eye of the user.

In some examples, the parametric curve fitting process may comprise an optimization algorithm that determines a curve having a minimum cost function **74**. The cost function **74** may be computed using each of the weighted pupil boundary point candidate **66**. In some examples, elements contributing to the cost function **74** may include a distance of the weighted pupil boundary point candidate **66** from the instant curve that is being optimized. In this manner, the number of weighted pupil boundary point candidates **66** lying on or very near the instant curve will be inversely proportional to the magnitude of cost function **74** for that curve.

In some examples, elements contributing to the cost function **74** may include a weight of each of the weighted boundary point candidates **66**. In this manner, weighted pupil boundary point candidates **66** with higher weights may contribute more to the value of the cost function **74**. As an example, where the distance of a weighted pupil boundary point candidate **66** is far from the instant parametric curve **70**, the magnitude of the cost function **74** will increase as the weight of the weighted pupil boundary point candidate **66** increases.

In some examples, elements contributing to the cost function **74** may include the magnitude of a discrepancy between an image-space gradient and a parametric curve normal for each of the weighted pupil boundary point candidates **66**. As an example, as the discrepancy increases between an image-space gradient of a weighted pupil boundary point candidate and a parametric curve gradient of a parametric curve at or near the weighted pupil boundary point candidate (which gradient will be normal or approximately normal to the pupil-iris boundary line), the magnitude of the cost function **74** will likewise increase. Correspondingly, as the discrepancy between the image-space gradient and the parametric curve gradient decreases, the magnitude of the cost function **74** will likewise decrease.

With reference now to FIGS. **12** and **13**, examples of image-space gradients for two weighted pupil boundary point candidates are provided. It will be appreciated that for a weighted pupil boundary point candidate **66** that is located at or near a parametric curve **70** that follows or closely approximates a pupil-iris boundary line, such candidate will have an image-space gradient pointing in a direction that is normal or approximately normal to the pupil-iris boundary line. Accordingly, as the color space of the eye image changes from the darker rough pupil region to the lighter iris region at the pupil-iris boundary line, such an image-space gradient will be roughly collinear with the gradient of such parametric curve at or near the weighted pupil boundary point candidate **66** (which will be normal or approximately normal to the pupil-iris boundary line).

For example and as schematically shown in FIG. **12**, a weighted pupil boundary point candidate **1204** is located along ray **1208** that extends from an estimated center of rough pupil region **1212**. The weighted pupil boundary point candidate **1204** is also located on a parametric curve **1216** that closely tracks a pupil-iris boundary between the rough pupil region **1212** and the iris region **1220** of the image. As shown in the example of FIG. **12**, an image space gradient **1222** of the weighted pupil boundary point candidate **1204** has a direction that is offset by T degrees from the direction of a parametric curve gradient **1224** that is normal to the curve **1216**. In some examples, such offset may increase the cost function by a factor of X.

Turning to the example of FIG. **13**, a weighted pupil boundary point candidate **1304** is located along ray **1208** and is spaced from parametric curve **1216**, thus representing a false positive. A glint **1308** is also located within the rough pupil region **1212**. In this example, weighted pupil boundary point candidate **1304** was selected at least in part due to its proximity to the glint **1308**. Because of the nearby and high contrast glint **1308**, an image space gradient **1312** of the weighted pupil boundary point candidate **1304** has a direction pointing towards the glint. Thus, in this example the image space gradient **1312** is offset by Y degrees from the direction of the parametric curve gradient **1224**, where Y is significantly greater than T. Accordingly, this larger offset increases the cost function by a factor of Z that is greater than X.

With reference now to FIG. **14** and upon fitting a parametric curve **1404** to the weighted pupil boundary point candidates **66**, the pupil detection module **18** may determine an estimated pupil region **1408** of the eye of a user.

With reference now to FIG. **15**, one example of an HMD device **1500** in the form of a pair of wearable glasses with a transparent display is provided. It will be appreciated that in other examples, the HMD device **1500** may take other suitable forms in which a transparent, semi-transparent, and/or non-transparent display is supported in front of a viewer's eye or eyes. It will also be appreciated that the HMD device **218** shown in FIG. **2** may take the form of the HMD device **1500**, as described in more detail below, or any other suitable HMD device.

The HMD device **1500** includes a display system **1502** and a see-through or transparent display **1504** that enables images such as holographic objects to be delivered to the eyes of a wearer of the HMD device. The transparent display **1504** may be configured to visually augment an appearance of a real-world, physical environment to a wearer viewing the physical environment through the transparent display. For example, the appearance of the physical environment may be augmented by graphical content (e.g., one or more pixels each having a respective color and brightness) that is presented via the transparent display **1504** to create an augmented reality environment.

The transparent display **1504** may also be configured to enable a wearer of the HMD device to view a physical, real-world object in the physical environment through one or more partially transparent pixels that are displaying a virtual object representation. In some examples the transparent display **1504** may include image-producing elements located within lenses **1506** (such as, for example, a see-through Organic Light-Emitting Diode (OLED) display). As another example, the transparent display **1504** may include a light modulator on an edge of the lenses **1506**. In this example, the lenses **1506** may serve as a light guide for delivering light from the light modulator to the eyes of a wearer. Such a light guide may enable a wearer to perceive a 3D holographic image located within the physical environment that the wearer is viewing, while also allowing the wearer to view physical objects in the physical environment, thus creating an augmented reality environment.

The HMD device **1500** may also include various sensors and related systems. For example, the HMD device **1500** may include an eye-tracking system **1508** that includes one or more image sensors configured to acquire image data in the form of gaze tracking data from a wearer's eyes. Provided the wearer has consented to the acquisition and use of this information, the eye-tracking system **1508** may use this information to track a position and/or movement of the wearer's eyes.

In one example, the eye-tracking system **1508** includes a gaze detection subsystem configured to detect a direction of gaze of each eye of a wearer. The gaze detection subsystem may be configured to determine gaze directions of each of a wearer's eyes in any suitable manner. For example, the gaze detection subsystem may comprise one or more light sources, such as infrared light sources **1510**, configured to cause a glint of light to reflect from the cornea of each eye of a wearer. One or more image sensors, such as inward facing sensor **1512**, then may be configured to capture an image of the wearer's eyes.

Images of the glints and of the pupils as determined from image data gathered from the image sensors may be used to determine an optical axis of each eye. Using this information, the eye-tracking system **1508** may then determine a direction the wearer is gazing. The eye-tracking system **1508** may additionally or alternatively determine at what physical or virtual object the wearer is gazing. Such gaze tracking data may then be provided to the HMD device **1500**. It will also be understood that the eye-tracking system **1508** may have any suitable number and arrangement of light sources and image sensors.

The HMD device **1500** may also include sensor systems that receive physical environment data from the physical environment. For example, the HMD device **1500** may also include a head tracking system **1514** that utilizes one or more pose sensors, such as pose sensors **1516** on HMD device **1500**, to capture head pose data and thereby enable position tracking, direction/location and orientation sensing, and/or motion detection of the wearer's head. Accordingly and as noted above, the head tracking system **1514** may receive sensor data from pose sensors **1516** that enable the orientation of the HMD device **1500** to be estimated in three degrees of freedom or the location and orientation of the HMD device to be estimated in six degrees of freedom.

In one example, head tracking system **1514** may comprise an inertial measurement unit (IMU) configured as a three-axis or three-degree of freedom position sensor system. This example position sensor system may, for example, include three gyroscopes to indicate or measure a change in orientation of the HMD device **1500** within 3D space about three orthogonal axes (e.g., x, y, and z, or roll, pitch, and yaw). The orientation derived from the sensor signals of the IMU may be used to display, via the transparent display **1504**, one or more virtual objects with a body-locked position in which the position of each virtual object appears to be fixed relative to the wearer of the see-through display and the position of each virtual object appears to be moveable relative to real-world objects in the physical environment.

In another example, head tracking system **1514** may comprise an IMU configured as a six-axis or six-degree of freedom position sensor system. This example position sensor system may, for example, include three accelerometers and three gyroscopes to indicate or measure a change in location of the HMD device **1500** along the three orthogonal axes and a change in device orientation about the three orthogonal axes.

The head tracking system **1514** may also support other suitable positioning techniques, such as GPS or other global navigation systems. Further, while specific examples of position sensor systems have been described, it will be appreciated that any other suitable position sensor systems may be used. For example, head pose and/or movement data may be determined based on sensor information from any combination of sensors mounted on the wearer and/or external to the wearer including, but not limited to, any number of gyroscopes, accelerometers, inertial measurement units, GPS devices, barometers, magnetometers, cameras (e.g., visible light cameras, infrared light cameras, time-of-flight depth cameras, structured light depth cameras, etc.), communication devices (e.g., WIFI antennas/interfaces), etc.

In some examples, the HMD device **1500** may also include an optical sensor system that utilizes one or more outward facing sensors, such as optical sensor **1518** on HMD device **1500**, to capture image data. The outward facing sensor(s) may detect movements within its field of view, such as gesture-based inputs or other movements performed by a wearer or by a person or physical object within the field of view. The outward facing sensor(s) may also capture 2D image information and depth information from the physical environment and physical objects within the environment. For example, the outward facing sensor(s) may include a depth camera, a visible light camera, an infrared light camera, and/or a position tracking camera.

The optical sensor system may include a depth tracking system that generates depth tracking data via one or more depth cameras. In one example, each depth camera may include left and right cameras of a stereoscopic vision system. Time-resolved images from one or more of these depth cameras may be registered to each other and/or to images from another optical sensor such as a visible spectrum camera, and may be combined to yield depth-resolved video.

In other examples, a structured light depth camera may be configured to project a structured infrared illumination, and to image the illumination reflected from a scene onto which the illumination is projected. A depth map of the scene may be constructed based on spacings between adjacent features in the various regions of an imaged scene. In still other examples, a depth camera may take the form of a time-of-flight depth camera configured to project a pulsed infrared illumination onto a scene and detect the illumination reflected from the scene. For example, illumination may be provided by an infrared light source **1520**. It will be appreciated that any other suitable depth camera may be used within the scope of the present disclosure.

The outward facing sensor(s) may capture images of the physical environment in which a wearer of the HMD device is situated. With respect to the HMD device **1500**, in one example an augmented reality display enhancement program may include a 3D modeling system that uses such captured images to generate a virtual environment that models the physical environment surrounding the wearer of the HMD device. In some embodiments, the optical sensor **1518** may cooperate with the IMU to determine the location and the orientation of the HMD device **1500** in six degrees of freedom. Such location and orientation information may be used to display, via the transparent display **1504**, one or more virtual objects with a world-locked position in which a position of each virtual object appears to be fixed relative to real-world objects viewable through the transparent display, and the position of each virtual object appears to be moveable relative to a wearer of the see-through display.

The HMD device **1500** may also include a microphone system that includes one or more microphones, such as microphone **1522**, that capture audio data. In other examples, audio may be presented to the wearer via one or more speakers, such as speaker **1524** on the HMD device **1500**.

The HMD device **1500** may also include a controller, such as controller **1526**. The controller **1526** may include a logic subsystem and a storage subsystem, as discussed in more detail below with respect to FIG. **17**, that are in communication with the various sensors and systems of the HMD device **1500**. In one example, the storage subsystem may include instructions that are executable by the logic subsystem to receive signal inputs from the sensors, determine a pose of the HMD device **1500**, and adjust display properties for content displayed via the transparent display **1504**.

FIGS. **16**A and **16**B illustrate a flow chart of a method **1600** for determining an estimated pupil region of an eye of a user according to an example of the present disclosure. The following description of method **1600** is provided with reference to the software and hardware components of the system **10** described above and shown in FIGS. **1-15**. It will be appreciated that method **1600** may also be performed in other contexts using other suitable hardware and software components.

With reference to FIG. **16**A, at **1604** the method **1600** may include receiving an image of the eye of the user, with the image comprising a plurality of pixels. At **1608** the method **1600** may include generating a rough pupil region using at least a subset of the plurality of pixels. At **1612** the method **1600** may include extracting one or more stable regions from the image. At **1616** the method **1600** may include identifying one or more maximally stable extremal regions in linear time.

At **1620** the method **1600** may include using one or more classifiers to classify each of the pixels of the subset of the plurality of pixels into one of a plurality of classification regions. At **1624** the method **1600** may include, where the rough pupil region comprises one or more connected components, scoring each of the connected components using a plurality of heuristics corresponding to different pupil characteristics.

At **1628** the method **1600** may include extracting from the rough pupil region a plurality of pupil boundary point candidates. With reference now to FIG. **16**B, at **1632** the method **1600** may include, for each of the pupil boundary point candidates, weighting the pupil boundary point candidate based on color values of at least two neighbor pixels of the pupil boundary point candidate to generate weighted pupil boundary point candidates. At **1636** the method **1600** may include determining a color value of each of a plurality of inner pixels located between the pupil boundary point candidate and an estimated center of the rough pupil region along a ray extending from the estimated center through the pupil boundary point candidate. At **1640** the method **1600** may include determining a color value of each of a plurality of outer pixels located along the ray, the plurality of outer pixels located on an opposite side of the pupil boundary point candidate from the inner pixels.

At **1644** the method **1600** may include averaging the color values of the plurality of inner pixels, and averaging the color values of the plurality of outer pixels. At **1648** the method **1600** may include clustering the pupil boundary point candidates in a two-dimensional color space according to their average color values of their inner pixels and their average color values of their outer pixels. At **1652** the method **1600** may include assigning a weight to each of the pupil boundary point candidates based on a distance of each of the pupil boundary point candidates from a center of a dominant cluster.

At **1656** the method **1600** may include fitting a parametric curve to the weighted pupil boundary point candidates to determine the estimated pupil region of the eye of the user. At **1660** the method **1600** may include minimizing a cost function that is computed using each of the weighted pupil boundary point candidates. At **1664** one or more elements contributing to the cost function may comprise one or more of a discrepancy between an image-space gradient and a parametric curve normal for each of the weighted pupil boundary point candidates, and a distance of each of the weighted pupil boundary point candidates from the parametric curve.

It will be appreciated that method **1600** is provided by way of example and is not meant to be limiting. Therefore, it is to be understood that method **1600** may include additional and/or alternative steps than those illustrated in FIGS. **16**A and **16**B. Further, it is to be understood that method **1600** may be performed in any suitable order. Further still, it is to be understood that one or more steps may be omitted from method **1600** without departing from the scope of this disclosure.

FIG. **17** schematically shows a nonlimiting embodiment of a computing system **1700** that may perform one or more of the above described methods and processes. Computing device **22** may take the form of or include one or more aspects of computing system **1700**. Computing system **1700** is shown in simplified form. It is to be understood that virtually any computer architecture may be used without departing from the scope of this disclosure. In different embodiments, computing system **1700** may take the form of a mainframe computer, server computer, desktop computer, laptop computer, tablet computer, home entertainment computer, network computing device, mobile computing device, mobile communication device, gaming device, etc.

As shown in FIG. **17**, computing system **1700** includes a logic subsystem **1704**, storage subsystem **1708**, and sensor subsystem **1712**. Computing system **1700** may optionally include a display subsystem **1716**, communication subsystem **1720**, input subsystem **1722** and/or other subsystems and components not shown in FIG. **17**. Computing system **1700** may also include computer readable media, with the computer readable media including computer readable storage media and computer readable communication media. Computing system **1700** may also optionally include other user input devices such as keyboards, mice, game controllers, and/or touch screens, for example. Further, in some embodiments the methods and processes described herein may be implemented as a computer application, computer service, computer API, computer library, and/or other computer program product in a computing system that includes one or more computers.

Logic subsystem **1704** may include one or more physical devices configured to execute one or more instructions. For example, the logic subsystem **1704** may be configured to execute one or more instructions that are part of one or more applications, services, programs, routines, libraries, objects, components, data structures, or other logical constructs. Such instructions may be implemented to perform a task, implement a data type, transform the state of one or more devices, or otherwise arrive at a desired result.

The logic subsystem **1704** may include one or more processors that are configured to execute software instructions. Additionally or alternatively, the logic subsystem may include one or more hardware or firmware logic machines configured to execute hardware or firmware instructions. Processors of the logic subsystem may be single core or multicore, and the programs executed thereon may be configured for parallel or distributed processing. The logic subsystem may optionally include individual components that are distributed throughout two or more devices, which may be remotely located and/or configured for coordinated processing. One or more aspects of the logic subsystem may be virtualized and executed by remotely accessible networked computing devices configured in a cloud computing configuration.

Storage subsystem **1708** may include one or more physical, persistent devices configured to hold data and/or instructions executable by the logic subsystem **1704** to implement the herein described methods and processes. When such methods and processes are implemented, the state of storage subsystem **1708** may be transformed (e.g., to hold different data).

Storage subsystem **1708** may include removable media and/or built-in devices. Storage subsystem **1708** may include optical memory devices (e.g., CD, DVD, HD-DVD, Blu-Ray Disc, etc.), semiconductor memory devices (e.g., RAM, EPROM, EEPROM, etc.) and/or magnetic memory devices (e.g., hard disk drive, floppy disk drive, tape drive, MRAM, etc.), among others. Storage subsystem **1708** may include devices with one or more of the following characteristics: volatile, nonvolatile, dynamic, static, read/write, read-only, random access, sequential access, location addressable, file addressable, and content addressable.

In some embodiments, aspects of logic subsystem **1704** and storage subsystem **1708** may be integrated into one or more common devices through which the functionally described herein may be enacted, at least in part. Such hardware-logic components may include field-programmable gate arrays (FPGAs), program- and application-specific integrated circuits (PASIC/ASICs), program- and application-specific standard products (PSSP/ASSPs), system-on-a-chip (SOC) systems, and complex programmable logic devices (CPLDs), for example.

FIG. **17** also shows an aspect of the storage subsystem **1708** in the form of removable computer readable storage media **1724**, which may be used to store data and/or instructions executable to implement the methods and processes described herein. Removable computer-readable storage media **1724** may take the form of CDs, DVDs, HD-DVDs, Blu-Ray Discs, EEPROMs, and/or floppy disks, among others.

It is to be appreciated that storage subsystem **1708** includes one or more physical, persistent devices. In contrast, in some embodiments aspects of the instructions described herein may be propagated in a transitory fashion by a pure signal (e.g., an electromagnetic signal, an optical signal, etc.) that is not held by a physical device for at least a finite duration. Furthermore, data and/or other forms of information pertaining to the present disclosure may be propagated by a pure signal via computer-readable communication media.

Sensor subsystem **1712** may include one or more sensors configured to sense different physical phenomenon (e.g., visible light, infrared light, sound, acceleration, orientation, position, etc.) as described above. Sensor subsystem **1712** may be configured to provide sensor data to logic subsystem **1704**, for example such data may include image information, ambient lighting information, depth information, audio information, position information, motion information, user location information, and/or any other suitable sensor data that may be used to perform the methods and processes described above.

When included, display subsystem **1716** may be used to present a visual representation of data held by storage subsystem **1708**. As the above described methods and processes change the data held by the storage subsystem **1708**, and thus transform the state of the storage subsystem, the state of the display subsystem **1716** may likewise be transformed to visually represent changes in the underlying data. The display subsystem **1716** may include one or more display devices utilizing virtually any type of technology. Such display devices may be combined with logic subsystem **1704** and/or storage subsystem **1708** in a shared enclosure, or such display devices may be peripheral display devices.

When included, communication subsystem **1720** may be configured to communicatively couple computing system **1700** with one or more networks and/or one or more other computing devices. Communication subsystem **1720** may include wired and/or wireless communication devices compatible with one or more different communication protocols. As nonlimiting examples, the communication subsystem **1720** may be configured for communication via a wireless telephone network, a wireless local area network, a wired local area network, a wireless wide area network, a wired wide area network, etc. In some embodiments, the communication subsystem may allow computing system **1700** to send and/or receive messages to and/or from other devices via a network such as the Internet.

When included, input subsystem **1722** may comprise or interface with one or more sensors or user-input devices such as a game controller, gesture input detection device, voice recognizer, inertial measurement unit, keyboard, mouse, or touch screen. In some embodiments, the input subsystem **1722** may comprise or interface with selected natural user input (NUI) componentry. Such componentry may be integrated or peripheral, and the transduction and/or processing of input actions may be handled on- or off-board. Example NUI componentry may include a microphone for speech and/or voice recognition; an infrared, color, stereoscopic, and/or depth camera for machine vision and/or gesture recognition; a head tracker, eye tracker, accelerometer, and/or gyroscope for motion detection and/or intent recognition; as well as electric-field sensing componentry for assessing brain activity.

The term "module" may be used to describe an aspect of the system **10** that is implemented to perform one or more particular functions. In some cases, such a module may be instantiated via logic subsystem **1704** executing instructions held by storage subsystem **1708**. It is to be understood that different modules may be instantiated from the same application, service, code block, object, library, routine, API, function, etc. Likewise, the same module may be instantiated by different applications, services, code blocks, objects, routines, APIs, functions, etc. The term "module" is meant to encompass individual or groups of executable files, data files, libraries, drivers, scripts, database records, etc.

It is to be understood that the configurations and/or approaches described herein are exemplary in nature, and that these specific embodiments or examples are not to be considered in a limiting sense, because numerous variations are possible. The specific routines or methods described herein may represent one or more of any number of processing strategies. As such, various acts illustrated may be performed in the sequence illustrated, in other sequences, in parallel, or in some cases omitted. Likewise, the order of the above-described processes may be changed.

The subject matter of the present disclosure includes all novel and nonobvious combinations and subcombinations of the various processes, systems and configurations, and other features, functions, acts, and/or properties disclosed herein, as well as any and all equivalents thereof.

The invention claimed is:

1. A method for determining an estimated pupil region of an eye of a user, the method comprising:

receiving an image of the eye of the user, the image comprising a plurality of pixels;

generating a rough pupil region using at least a subset of the plurality of pixels;

extracting from the rough pupil region a plurality of pupil boundary point candidate pixels;

for each of the pupil boundary point candidate pixels, weighting the pupil boundary point candidate pixel based on color values of at least two neighbor pixels of the pupil boundary point candidate pixel to generate weighted pupil boundary point candidates; and

fitting a parametric curve to the weighted pupil boundary point candidates to determine the estimated pupil region of the eye of the user.

2. The method of claim **1**, wherein weighting each of the pupil boundary point candidate pixels based on color values of at least two neighbor pixels further comprises:

determining a color value of each of a plurality of inner pixels located between the pupil boundary point candidate pixel and an estimated center of the rough pupil region along a ray extending from the estimated center through the pupil boundary point candidate pixel; and

determining a color value of each of a plurality of outer pixels located along the ray, the plurality of outer pixels located on an opposite side of the pupil boundary point candidate pixel from the inner pixels.

3. The method of claim **2**, wherein weighting each of the pupil boundary point candidate pixels based on color values of at least two neighbor pixels further comprises averaging the color values of the plurality of inner pixels, and averaging the color values of the plurality of outer pixels.

4. The method of claim **2**, wherein weighting each of the pupil boundary point candidate pixels further comprises:

clustering the pupil boundary point candidate pixels in a two-dimensional color space according to an average color value of their inner pixels and an average color value of their outer pixels; and

assigning a weight to each of the pupil boundary point candidate pixels based on a distance of each of the pupil boundary point candidate pixels from a center of a dominant cluster in the two-dimensional color space.

5. The method of claim **1**, wherein fitting the parametric curve to the weighted pupil boundary point candidates further comprises:

minimizing a cost function that is computed using each of the weighted pupil boundary point candidates.

6. The method of claim **5**, wherein one or more elements contributing to the cost function comprise one or more of a discrepancy between an image-space gradient and a parametric curve normal for each of the weighted pupil boundary point candidates, and a distance of each of the weighted pupil boundary point candidates from the parametric curve.

7. The method of claim **1**, wherein generating a rough pupil region further comprises extracting one or more stable regions from the image.

8. The method of claim **7**, wherein extracting one or more stable regions from the image further comprises identifying one or more maximally stable extremal regions.

9. The method of claim **1**, wherein generating a rough pupil region further comprises using one or more classifiers to classify each of the pixels of the subset of the plurality of pixels into one of a plurality of classification regions.

10. The method of claim **1**, wherein the rough pupil region comprises one or more connected components, and the method further comprises scoring each of the connected components using a plurality of heuristics corresponding to different pupil characteristics.

11. A system for determining an estimated pupil region of an eye of a user, the system comprising:

a computing device; and

a pupil detection module executed by a processor of the computing device, the pupil detection module configured to:

receive an image of the eye of the user, the image comprising a plurality of pixels;

generate a rough pupil region using at least a subset of the plurality of pixels;

extract from the rough pupil region a plurality of pupil boundary point candidate pixels;

for each of the pupil boundary point candidate pixels, weight the pupil boundary point candidate pixel based on color values of at least two neighbor pixels of the pupil boundary point candidate pixel to generate weighted pupil boundary point candidates; and

fit a parametric curve to the weighted pupil boundary point candidates to determine the estimated pupil region of the eye of the user.

12. The system of claim **11**, wherein to weight each of the pupil boundary point candidate pixels based on the color values of at least two neighbor pixels, the pupil detection module is further configured to:

determine a color value of each of a plurality of inner pixels located between the pupil boundary point candidate pixel and an estimated center of the rough pupil region along a ray extending from the estimated center through the pupil boundary point candidate pixel; and

determine a color value of each of a plurality of outer pixels located along the ray, the plurality of outer pixels located on an opposite side of the pupil boundary point candidate pixel from the inner pixels.

13. The system of claim **12**, wherein to weight each of the pupil boundary point candidate pixels based on the color values of at least two neighbor pixels, the pupil detection module is further configured to:

average the color values of the plurality of inner pixels, and average the color values of the plurality of outer pixels.

14. The system of claim **12**, wherein to weight each of the pupil boundary point candidate pixels based on the color values of at least two neighbor pixels, the pupil detection module is further configured to:

cluster the pupil boundary point candidate pixels in a two-dimensional color space according to their inner pixel values and their outer pixels values; and

assign a weight to each of the pupil boundary point candidate pixels based on a distance of each of the pupil boundary point candidate pixels from a center of a dominant cluster in the two-dimensional color space.

15. The system of claim **11**, wherein to fit the parametric curve to the weighted pupil boundary point candidates, the pupil detection module is further configured to minimize a cost function that is computed using each of the weighted pupil boundary point candidates.

16. The system of claim **15**, wherein one or more elements contributing to the cost function comprise one or more of a discrepancy between an image-space gradient and a parametric curve normal for each of the weighted pupil boundary point candidates, and a distance of each of the weighted pupil boundary point candidates from the parametric curve.

17. The system of claim **11**, wherein to generate a rough pupil region the pupil detection module is further configured to extract one or more stable regions from the image.

18. The system of claim **17**, wherein to extract one or more stable regions from the image the pupil detection module is further configured to identify one or more maximally stable extremal regions.

19. The system of claim **11**, wherein to generate a rough pupil region the pupil detection module is further configured to use one or more classifiers to classify each of the pixels of the subset of the plurality of pixels into one of a plurality of classification regions.

20. A method for determining an estimated pupil region of an eye of a user, the method comprising:

receiving an image of the eye of the user, the image comprising a plurality of pixels;

generating a rough pupil region using at least a subset of the plurality of pixels;

extracting from the rough pupil region a plurality of pupil boundary point candidates;

weighting each of the pupil boundary point candidates to generate weighted pupil boundary point candidates, wherein weighting each of the pupil boundary point candidates comprises:

determining a color value of each of a plurality of inner pixels located between the pupil boundary point candidate and an estimated center of the rough pupil region along a ray extending from the estimated center through the pupil boundary point candidate; and

determining a color value of each of a plurality of outer pixels located along the ray, the plurality of outer pixels located on an opposite side of the pupil boundary point candidate from the inner pixel; and

fitting a parametric curve to the weighted pupil boundary point candidates to determine the estimated pupil region of the eye of the user.

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